

Integration over song classification replicates: Song variant analysis in the hihi

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(Received 12 May 2014; revised 30 March 2015; accepted 9 April 2015)

Human expert analyses are commonly used in bioacoustic studies and can potentially limit the reproducibility of these results. In this paper, a machine learning method is presented to statistically classify avian vocalizations. Automated approaches were applied to isolate bird songs from long field recordings, assess song similarities, and classify songs into distinct variants. Because no positive controls were available to assess the true classification of variants, multiple replicates of automatic classification of song variants were analyzed to investigate clustering uncertainty. The automatic classifications were more similar to the expert classifications than expected by chance. Application of these methods demonstrated the presence of discrete song variants in an island population of the New Zealand hihi (*Notiomystis cincta*). The geographic patterns of song variation were then revealed by integrating over classification replicates. Because this automated approach considers variation in song variant classification, it reduces potential human bias and facilitates the reproducibility of the results. © 2015 Acoustical Society of America.

[<http://dx.doi.org/10.1121/1.4919329>]

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Pages: 2542–2551

I. INTRODUCTION

Many bioacoustic studies rely on accurate classifications of animal vocalizations recorded in the field. For example, similarities between avian sound signals are estimated and patterns of variation can be attributed to shared genetic ancestry (de Kort and ten Cate, 2001), shared learning template (Bond and Diamond, 2005), or shared environmental pressures on sound production (Slabbekoorn and den Boer-Visser, 2006). Bioacoustic analyses, once put into context, can, for example, be used to monitor species distribution (Dawson and Efford, 2009), study population connectivity (Irwin *et al.*, 2001), or show evidence for song learning (Podos and Warren, 2007). Therefore, it is critical to reliably measure sound similarities especially when a large number of recordings are being analyzed. Moreover, one needs to minimize any bias that could be introduced by the specific sensory attributes of human experts, which could preclude reproducibility of the analysis (Milinski, 1997; Giret *et al.*, 2011). For example, inconsistency across investigators has been reported in the classification of humpback whale songs (Cholewiak *et al.*, 2013).

A common approach to limit human biases in bioacoustic signal classification is to use automatic clustering methods on selected acoustic parameters. For example, artificial neural networks (ANNs) have been shown to statistically classify bat calls at the species level as accurately as human experts (Jennings *et al.*, 2008). Linear discriminant analysis (LDA) has also been used to identify shared call variants in captive red crossbills (Sewall, 2009), but expert knowledge had to be incorporated to finalize the classification. While LDA can help identify the acoustic parameters that best discriminate between individuals (Wanker and Fischer, 2013), the relevance of these parameters cannot be evaluated *a priori* when no information is available to estimate classification accuracy. When classifying reoccurring motifs constituting the vocalization of a single individual, e.g., bird song variants, the “true” classification of these variants is unknown. In that case, no controls are available to select the most relevant features of the songs to be used to define variants. In behavioral studies, one needs to focus on variants to which the species under study is sensitive. Variants that can be found by comparing parameters not perceived by that species may lead to false conclusions. Although the different variants defined according to these parameters could potentially be perceived differently by the human ear,

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they would, for instance, have no effect on the animal song acquisition through learning. Therefore, particular care needs to be taken in categorizing song elements in behavioral research. Ideally, laboratory tests are performed to analyze how the bird's sensory system responds to song signals (Margoliash, 2002), but this is often not feasible, in particular, for endangered species. Without any psychoacoustic study available, it remains difficult to select the parameters that are most important for the acoustic sensory system of a given species.

We utilize, here, an automatic method to measure acoustic similarities and classify bird vocalizations in an effort to limit prior selection of sound features, avoid human bias, and offer a way to achieve reproducible bioacoustic analysis. Combinations of speech recognition sound parameters and ANNs have been used to perform individual recognition in primate calls (Mielke and Zuberbühler, 2013) and identify recurring sound pattern in humpback whale songs (Green *et al.*, 2011) with high accuracy. In particular, intraspecific song variation in the white-crowned sparrow (Ranjard and Ross, 2008) and antbirds (Vallejo *et al.*, 2007; Kirschel *et al.*, 2009) have previously been described using this type of automatic clustering approach. Here, an updated version of the evolving tree neural network song classifier (Ranjard and Ross, 2008) is described with a modified neighborhood size function definition. We use a representation of the full spectrogram of the songs rather than selected parameters to automatically isolate and classify song variants. Song signals are encoded as mel frequency cepstrum (Davis and Mermelstein, 1980) and perceptual linear predictive coding coefficients (Hermansky, 1990). Such representations, even though originally designed to study the human voice, have now successfully been applied to multiple studies of animal vocalizations (Clemins and Johnson, 2006; Ranjard and Ross, 2008; Tao *et al.*, 2008), including field-based research (Mielke and Zuberbühler, 2013; Potamitis *et al.*, 2014). Moreover, song acoustic distances can be quantitatively measured by aligning pairs of encoded songs. The distance between two songs, encoded as time sequences of coefficients, is derived from a dynamic time warping algorithm that searches for a nonlinear optimal match between the sequences. From the resulting alignment, the edit distance is defined as the number of operations required to transform one sequence into the other (Ranjard *et al.*, 2010; Krull *et al.*, 2012). This acoustic distance measure is incorporated in a machine learning classifier to automatically cluster the songs into variants. The classifier is structured as an evolving tree self-organizing map (SOM; Kohonen, 1990) ANN (Ranjard and Ross, 2008). The two main advantages of this approach are that (i) the nodes of the classifier are structured as a binary tree, which result in lower time complexity for computation, and (ii) unlike the classic SOM, the size of the network is not constant and, thus, the number of clusters is not defined *a priori*, but results from the specific properties of the set of songs being classified.

We use a set of automatic computational approaches to analyze songs of a population of the New Zealand hihi (*Notiomystis cincta*). First, male songs are isolated from audio recordings using hidden Markov models (HMMs).

Second, we test for the presence of song variants in the hihi by studying patterns of song variation. Third, we use an implementation of the evolving tree neural network to catalog the song variants. Male songs are then classified into the closest variants, which allows us to characterize the song repertoire of each individual. Finally, we examine geographic variation in the song repertoires by comparing distances separating male territories to a distance characterizing repertoire overlaps. The distribution of the correlation between these two distances is estimated by integrating over multiple classification replicates.

II. MATERIALS AND METHODS

A. Study species and song recordings

The hihi is an endemic New Zealand passerine. Few studies report information about hihi vocal behavior with only one carried out on the reintroduced Tiritiri Matangi Island population (Withers, 2005). This predator-free island is located off the coast of the North Island of New Zealand (36.60°S 174.89°E) and is composed of regenerating native forest. While both males and females produce calls associated with different behaviors, only males sing (Higgins *et al.*, 2001). The male song consists of a short, loud, high-pitched whistle involving two to three beats (Higgins *et al.*, 2001; Withers, 2005). During a song bout, a single male produces several variations of songs (Higgins *et al.*, 2001), or song variants as defined by their fine scale structural variation (Withers, 2005), that are drawn from its song repertoire. Songs are thought to be mainly territorial in function, being produced within the territory boundaries, and increasing in rate at periods of high competition for mating opportunities (Castro *et al.*, 1996; Higgins *et al.*, 2001; Withers, 2005).

Songs from 22 individual males were recorded on Tiritiri Matangi Island in the summers of 2004 and 2005 (Withers, 2005). Recordings were made using a digital audio tape recorder at 44.1 kHz with 16-bit precision. All birds were uniquely color banded and each male territory was documented. Territories were centered on artificial nest boxes and their locations were estimated using global positioning system (GPS) fixes of the nest boxes.

B. Song extraction

Model-based detectors have been reported to perform better than energy-based detectors (Skowronski and Harris, 2006). In the present study, songs were extracted from field recordings using a HMM recognizer (Young *et al.*, 2006), which allowed us to isolate vocalizations from background noise (Brandes, 2008; Trifa *et al.*, 2008). Recordings were encoded using 20 mel-cepstrum coefficients (MFCCs) plus the C0th cepstral parameter as the energy feature and the first order temporal derivatives. A window of 20 ms was used and no cepstral mean normalization was performed. All transitions were allowed between the six states of each HMM and the states were modeled as a mixture of four Gaussian density functions. Five models were manually defined, aiming to represent background noise and other bird

species' calls, human voice, hihi songs, silence, and recording device generated signals.

Recognition efficiency was assessed using a 24 min tape recording. For that recognition test, the tape was first annotated by a human expert who identified seven hihi songs. The automatic recognizer extracted a total of nine songs, including the seven hihi songs identified manually, a saddle-back song syllable (*Philesturnus carunculatus*), as well as an unidentified low amplitude bird vocalization. These two false positive signals have similar frequency distribution and duration as a typical hihi song.

After running the automatic recognizer on the full set of recordings (~27.7 h), each extracted song was visually checked using a custom graphical user interface in MATLAB (MathWorks, Natick, MA) to eliminate poor quality and noisy hihi songs, as well as other types of hihi calls. Both male and female hihi can produce a great variety of calls (Higgins *et al.*, 2001). In particular, contact calls are frequent vocalizations with similar frequency distribution, although slightly less modulated and shorter than male songs. In total, 590 extracted vocalizations were discarded. The extraction approach allowed us to construct a library containing a total of 1879 high quality adult male songs.

C. Preliminary analysis of song variation

1. Song encoding for classification

For classification, songs were represented as sequences of 12 MFCCs and 12 perceptual linear prediction coefficient (PLP) vectors. The C0th cepstral parameter was used as the energy feature. Cepstral mean normalization was performed on both sets of coefficients by estimating the mean across each song file. The first of the 26 filterbank channels was set at 1 kHz and the last one terminated at 20 kHz. This allowed us to filter out low-frequency content of the signal, which is generally not relevant for hihi vocalization analysis; hihi songs mostly contain energy between 2 kHz and 13 kHz (Withers, 2005). Under a sampling frequency of 44.1 kHz, a Hamming window of 128 samples, i.e., a frequency resolution of ~345 Hz, with 50% overlap was used for computing the spectra and the signal had first order pre-emphasis applied using a coefficient of 0.97. Two frames prior to and two frames following the current frame were used to estimate the first temporal derivative of each coefficient. Energy normalization was implemented by subtracting the maximum value of the energy and adding 1.0. The cepstral coefficients were re-scaled by liftering the cepstra using a coefficient of 22 so that they had similar magnitudes (Rabiner, 1993). As a result, each song was encoded as a time sequence of 50-parameter vector frames.

2. Song pairwise distances

As a first exploratory analysis, the presence of song variants was investigated by measuring bioacoustic similarities across a subset of extracted song recordings. This preliminary analysis was performed to investigate the general patterns of hihi song variation. It allowed us to test whether songs group into similar sets, i.e., song variants, which

would justify the use of a cluster analysis approach. A pairwise distance measure was calculated and represented as a dendrogram to investigate grouping structure.

In the case of discrete variants, songs are expected to group based on their acoustic characteristics. The acoustic distances measured between songs belonging to the same variant are expected to be smaller than distances to other songs. On the other hand, in the absence of song variants, no particular grouping of songs is expected and the acoustic distance is expected to vary continuously. A pairwise bioacoustic distance was calculated using dynamic time warping (Ranjard *et al.*, 2010). The resulting distance matrix was represented on a dendrogram using a neighbor-joining algorithm for a subset of 469 songs.

D. Song classification using ANN

The full dataset of songs was analyzed using a self-organizing ANN classifier (Ranjard and Ross, 2008). This algorithm aims at automatically identifying clusters of similar songs, removing the need for prior incorporation of information about the number of clusters, i.e., the number of song variants. The neural network is a type of growing SOM (Kohonen, 1990), derived from the evolving tree SOM (Pakkanen, 2004), which takes advantage of dynamic time warping (Ranjard *et al.*, 2010) to compute the weight matrices (Krull *et al.*, 2012) and calculate distances between the weight matrices and the songs to be classified. The classification is performed as a two-step process. First, the neural network is constructed and, second, the songs are grouped according to the resulting classification tree.

1. Network training

We implemented an evolving neural network classifier as specified in Ranjard and Ross (2008). For completeness, the full network specifications are included below. A set of M songs, S , is classified using a network defined as a set of connected weight matrices, W_t , at epoch, t . The neighborhood function is

$$h(W_t(x), S(y)) = \alpha(t) \exp\left(\frac{-d(W_t(x), S(y))^2}{2\sigma(t)^2}\right), \quad (1)$$

where $d(W_t(x), S(y))$ is the dynamic time warping distance between the neuron weight matrix, $W_t(x)$, and the sample, $S(y)$. The learning rate $\alpha(t)$ is

$$\alpha(t) = \max\left\{\alpha(0) \exp\left(\frac{-t^2}{(0.75T)^2}\right), \alpha_{\min}\right\}, \quad (2)$$

where T is the total number of epochs for learning. In comparison to Ranjard and Ross (2008), we slightly modified the neighborhood size function, $\sigma(t)$, which is now modeled as a Gaussian distribution, defined as

$$\sigma(t) = \sigma_{\max} \exp\left(\frac{-t - \frac{T+1}{2}}{2\sigma_{sd}^2}\right), \quad (3)$$

where σ_{\max} is the maximum value for the neighborhood size function and σ_{sd} is the standard deviation. Consequently, the neighborhood size function has a small value at the beginning of the learning process when the network is small and growing, larger values when the network self-organizes, and then small values toward the end, allowing the fine-tuning of the neuron weight matrices (Fig. 1). The number of children, or leaf number, is

$$n(t+1) = \max \left\{ n(t) - \frac{n(t)}{T}, n_{\min} \right\} \quad (4)$$

and therefore be set to decrease through the learning process. The counter of each neuron is $\text{count}(c(t+1)) = \gamma \text{count}(c(t))$. The weight decay, γ , restricts the size of the tree; see Pakkanen (2004) for details.

2. Classification into song variants

Once the network has been constructed and trained on a given dataset, classification of the songs is performed using the network weight matrices as cluster centroids, each representing different song variants. For each song, $S(y)$, the best matching neuron is found across the tips of the network at a given depth, so that it minimizes $d(S(y), W_p)$, where W_p is the set of weight matrices in the tree at depth, p . Figure 2 illustrates the learning and classification processes of the network. A MATLAB (MathWorks, Natick, MA) library for this implementation, *dwave_cluster*, is available.¹

E. Classification evaluation

The accuracy and precision of the automatic neural network classification were assessed using the repertoire of a single individual. The song repertoire (20 song recordings; Fig. 3) was classified into song variants by experts (LR, SJW, and HR) using spectrogram shapes and audio recordings. These three expert classifications were compared to repeated automatic classifications obtained with the ANN and to multiple random classifications of these 20 songs.

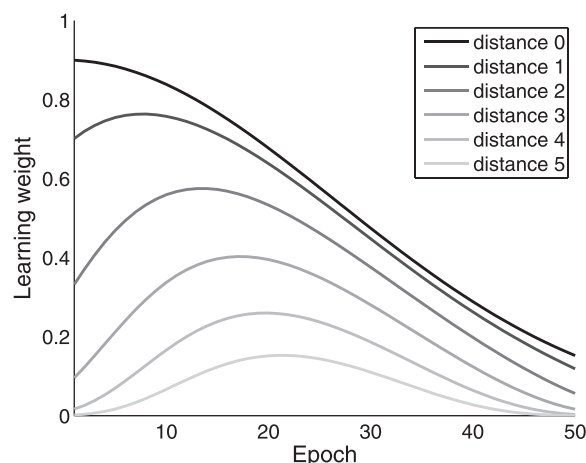


FIG. 1. Learning weight in the neural network during a 50 epochs learning process with a neighborhood strength function modeled as a Gaussian for different distances from the best matching unit in the network.

Neural network classification is not deterministic (Ranjard and Ross, 2008), therefore, 100 ANN classification replicates were computed using the parameters listed in Table I to investigate consistency. A total of 100 random classifications were constructed by randomly assigning songs to n clusters, with $n = \mathcal{N}(9, 4)$. The Rand index, RI (Rand, 1971), and Jaccard index, JI (Jaccard, 1908), were calculated to assess agreement both within and between the experts, neural network, and random classifications. When comparing classification C_1 to classification C_2 , these indexes are defined as $\text{JI} = a/(a+b+c)$ and $\text{RI} = (a+d)/(a+b+c+d)$, with a : number of pairs of songs classified together in both C_1 and C_2 , b : number of pairs of songs classified together in C_1 , but not in C_2 , c : number of pairs of songs classified together in C_2 , but not in C_1 , and d : number of pairs of songs that are not classified together in either C_1 nor C_2 .

The JI does not take into account the number of pairs, d , that are separated in both classifications. Both indexes are defined from 0 to 1, with high value indicating high similarity between two classifications.

F. Correlation between geographic distance and song repertoires

The full dataset of 1879 songs was classified into song variants using the ANN classifier, constructed using the parameter values listed in Table II. A total of 100 classification replicates were completed to take into account the variation in the clustering signal of the song acoustic parameters. For each replicate, the classification tree rules are potentially defined according to different features of the extracted acoustic parameters.

Different levels of classification, i.e., different numbers of clusters, can be defined by selecting different depths in the evolving tree. For each level, the number of clusters and the intra-cluster distance were calculated (see Fig. 4 for an example on a single classification). With large depth values, high numbers of clusters are defined and the mean intra-cluster distance is low, showing high similarity between songs grouped in the same cluster. However, the resulting classification may be poor when distinct cluster centroids are too similar, as shown by high values for the Davies–Bouldin clustering index (Davies, 1979). A depth of 4 in all classifications was selected to minimize this index, as well as the number of clusters and the mean largest intra-cluster distances. Finally, the repertoire of each bird was defined as the set of song variants that it sang.

To determine whether micro-geographic patterns of song sharing were present on Tiritiri Matangi, we evaluated the proportion of shared song variants between territories by calculating the Jaccard distance between every pair of territories. This generated a territory song content pairwise distance matrix (30×30) that could be compared to the geographic distance between the territories. The Pearson product-moment correlation coefficient was calculated for each classification replicate, allowing us to obtain an estimated distribution for the correlation between geographic and repertoire distances.

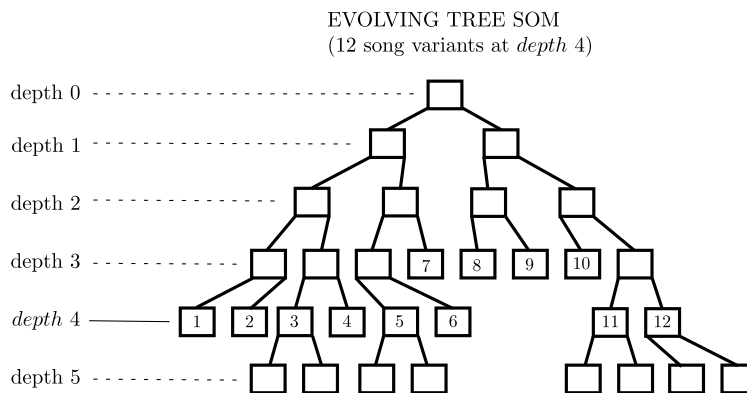
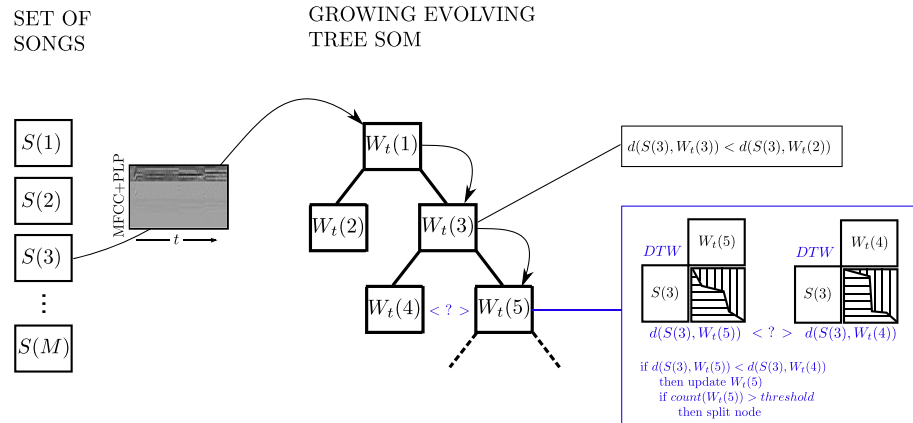


FIG. 2. (Color online) General framework for one automatic song classification using the evolving tree ANN. First, the network is trained on the whole set of songs, S , then classification is performed to define song variants. (A) Training: At each epoch, all samples from S are chosen once in a random order, encoded as a time sequence of MFCC and PLP coefficients. For each sample, the best matching tip in the classification tree is found by starting from the root of the tree and going down through each level. A dynamic time warping (DTW) algorithm provides a distance between the sample and the two weight matrices, W , at the current level in the tree, determining the next level to be tested. Once a tip is reached, the weight matrices, W , are updated applying the Kohonen learning rule. In the illustrated example, the classification tree contains five nodes at epoch t . When the song $S(3)$ is chosen, $d(S(3), W_t(3)) < d(S(3), W_t(2))$ and the next levels to test are therefore $W_t(4)$ and $W_t(5)$. If $d(S(3), W_t(5)) < d(S(3), W_t(4))$ and $\text{count}(W_t(5))$ is greater than a predefined splitting threshold, then the tree is extended by subdividing the node, $W_t(5)$, with two new daughter nodes and weight matrices. (B) Classification: After training, a tree depth is selected and each tip of the network at this depth represents a song variant. Each song from S is classified by using DTW to find the closest weight matrix and define the song variant. In the example, depth 4 is selected at which 12 song variants can possibly be described. Note that some of the tips of the tree may not be attributed to any song, resulting in a smaller number of variants than the total number of tips.

III. RESULTS

The neighbor-joining tree representing the pairwise distances measured between the subset of 469 songs shows songs grouping into independent clusters (Fig. 5). The bioacoustic dynamic time warping distance between these songs is, therefore, not continuously distributed and indicates that smaller distances were obtained between songs belonging to the same cluster. Several clusters of songs were identified in the tree for which the spectrogram shapes appear visually consistent (Fig. 5). However, the relationships between these clusters are not precisely defined, with each being placed at approximately the same distance from all the other clusters.

The highest clustering similarities were reported between replicates of the neural network classifications ($\overline{\text{JI}} = 0.382$, $\overline{\text{RI}} = 0.927$), which demonstrates high consistency within these automatic classifications (Fig. 6). The lowest agreement was found within random classifications and between random and other classifications. Agreement

between expert and neural network classifications was relatively high ($\overline{\text{JI}} = 0.314$, $\overline{\text{RI}} = 0.888$) and higher on average than within expert classifications ($\overline{\text{JI}} = 0.285$, $\overline{\text{RI}} = 0.860$). Although fewer expert classifications was performed, the 95% interval range of the index values, $[0.816, 0.905]$ for RI, shows that low agreement can be observed between experts at a level that is not found in the 100 neural networks replicated classifications, 95% interval is $[0.884, 0.968]$. However, the interval of value for each index is large, e.g., $[0.155, 0.578]$ for JI, but consistently higher than values obtained against the random classifications ($[0.000, 0.155]$).

The automatic neural network classifications of the total dataset resulted in 16 clusters, which were used to define 16 different song variants. On average, each male has a repertoire containing 9.1 song variants. The distribution of the correlation coefficient between the geographic distance and the Jaccard distance shows a low level of positive correlation (Fig. 7) with the mean equal to 0.11.

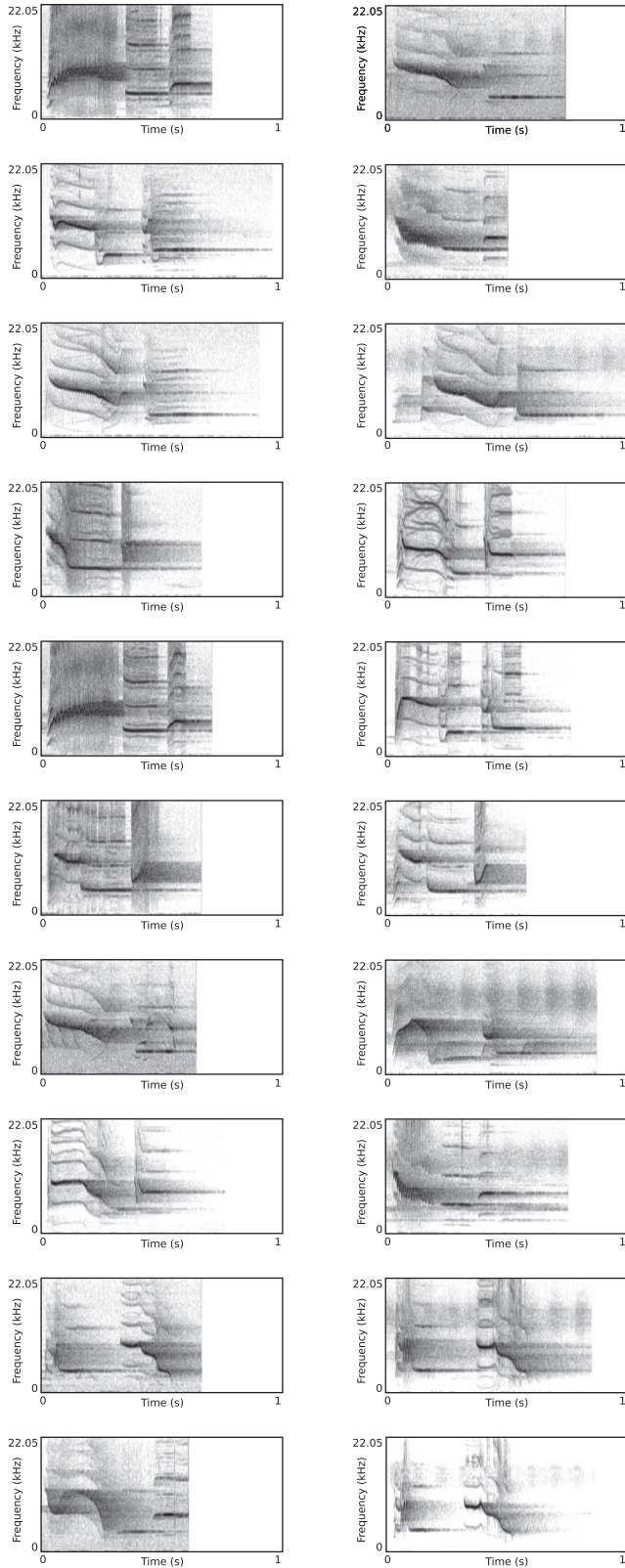


FIG. 3. Song repertoire of a single male used for classification tests. Songs are not ordered in any particular way. Spectrograms range from 0 to 22 050 Hz (fast Fourier transform, 256 bands; window, Gaussian 50% overlap; frequency resolution, 86 Hz; temporal resolution, 5 ms).

IV. DISCUSSION

Only a limited number of bioacoustic studies (Stoddard *et al.*, 1988; Podos *et al.*, 1992; Searcy *et al.*, 1995; Deecke

TABLE I. ANN parameter values used for the automatic classification of songs for classification evaluation.

Parameter	Value
Number of epochs	5
Splitting threshold	2
Neighborhood strength maximum	4
Neighborhood strength standard deviation	2
Initial leaf number	2
Final leaf number	2
Gamma	0.95
Initial learning rate	0.90
Final learning rate	0.01

and Janik, 2006; Gamba and Giacoma, 2007; Green *et al.*, 2011) test for the presence and the biological relevance of categories in animal vocalizations (Searcy *et al.*, 1999). However, such investigation is necessary before forming hypotheses regarding the biological meaning of these patterns (Hauser, 1997). Our results demonstrate the presence of distinct song variants in the male repertoires of the Tiritiri Matangi Island hihi population. While the methodological approach used to identify these variants is of primary importance, no positive controls are available to assess its accuracy as the song clusters perceived by the birds and, therefore, of biological relevance, remain unknown. Consequently, in order to identify song clusters, we compare automatic and human-based clustering methods by assessing their consistency and agreement against randomly structured classifications. We define an ANN approach that is consistent and can reproduce part of the variation found in human expert classifications offering a way to overcome limitations of human-based analyses. The ANN song classification shows that the constitutive elements of the male repertoires, defined as their spectro-temporal representations, can be shared across individuals. These variants are distinguishable on the basis of their time-frequency parameters as defined by MFCC and PLP coefficients, although our approach can be applied to other sound features. The dynamic time warping distance, which measures subtle changes in the frequency distribution of the songs, is able to efficiently quantify the differences across variants.

Both the detection and classification of song variants are automatically performed. The combination of MFCC coefficients with an HMM model provides an accurate approach

TABLE II. ANN parameter values used for the automatic classification of songs (full dataset).

Parameter	Value
Number of epochs	15
Splitting threshold	94
Neighborhood strength maximum	4
Neighborhood strength standard deviation	2
Initial leaf number	2
Final leaf number	2
Gamma	0.95
Initial learning rate	0.90
Final learning rate	0.01

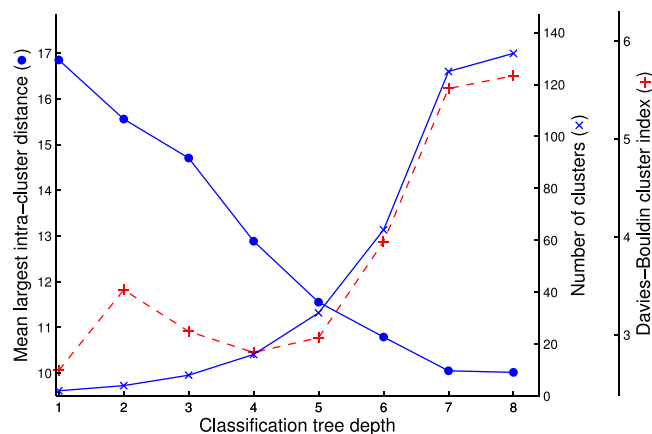


FIG. 4. (Color online) Mean largest intra-cluster distance decreases with the depth in the classification tree during the learning process. The Davies-Bouldin clustering index is also indicated.

for extracting hihi calls from field recordings. In the present study, the detector allows us to successfully isolate hihi vocalizations from background noise and other species calls that are potentially produced at high energy. Additionally, manual removal is carried out to ensure high quality of the song dataset. During this process, (i) songs with overlapping bioacoustic signal or background noise and (ii) other types of hihi calls are discarded. To limit further the manual selection of extracted songs, a HMM specific to each hihi call type could be added to the recognizer. Recent results suggest that bandpass filtering prior to song encoding (Potamitis *et al.*, 2014) and the use of general acoustic features that incorporate animal perceptual information (Clemins and Johnson, 2006; Bastas *et al.*, 2012) may improve the detection accuracy. Furthermore, identifying, e.g., through laboratory experiments (Dooling *et al.*, 2002), and focusing only on the acoustic parameters to which birds are the most sensitive could enhance the detection accuracy. Similarly, such sound features could also be used to improve the song classification procedure.

We present an automatic clustering approach to perform song variant classification when only limited prior knowledge is available. As opposed to individual identification or species recognition problems, no dataset can be referenced to act as a classification control. In this case, unless the variants can be associated to a specific behavioral context, e.g., flight calls (Keen *et al.*, 2014), or convey an observable information, e.g., social categories (Wanker and Fischer, 2013), it is not possible to assess classification accuracy against a known “true” classification. Consequently, a classifier error rate cannot be estimated. Therefore, we focus on consistency across classification replicates, as well as agreement between human and automatic classifiers to evaluate classifiers. We report relatively low agreement between human expert classifications on the test dataset. Therefore, there is a level of uncertainty in the grouping of the songs preventing the use of a single benchmark expert classification to (i) optimize the song variant classifier (Trawicki *et al.*, 2005; Tao *et al.*, 2008) and (ii) select the best acoustic parameters using, for example, a feature generation approach (Giret *et al.*, 2011). We, therefore, define an unsupervised

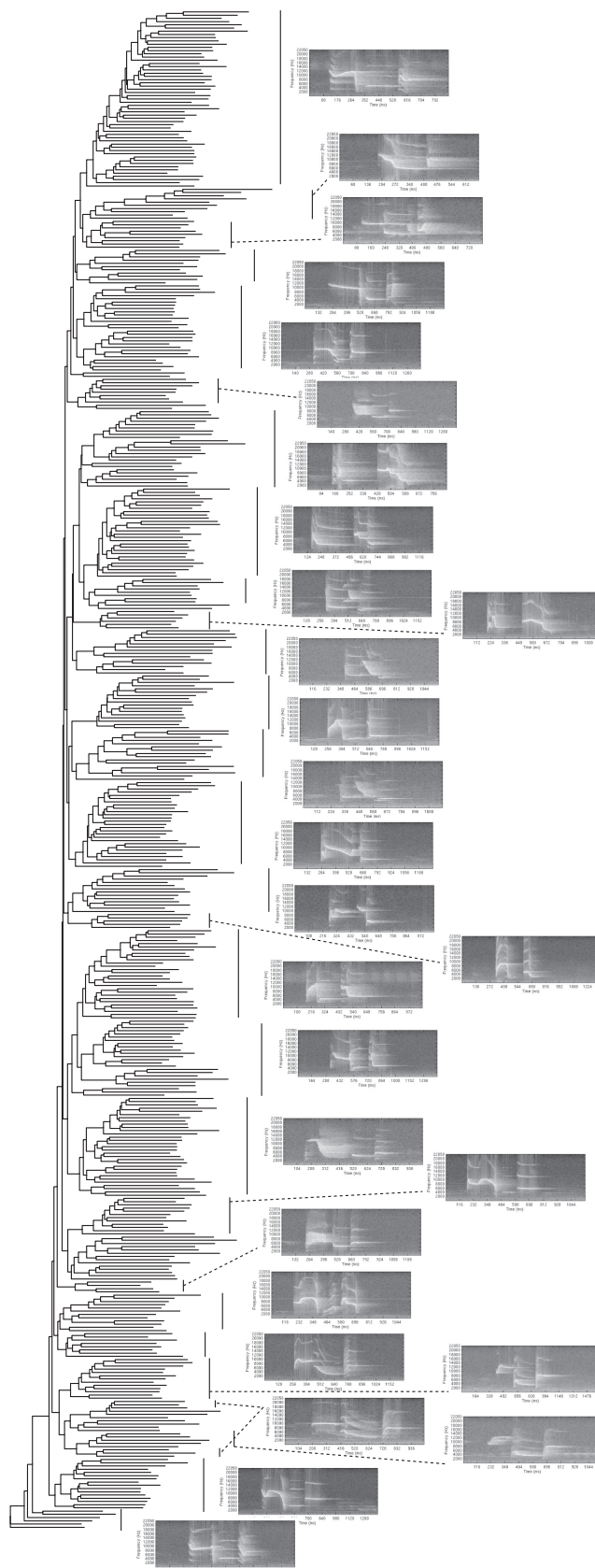


FIG. 5. Neighbor-joining dendrogram showing the pairwise song distances obtained from encoded spectrogram alignments of a subset of 469 songs. Using visual inspection, a vertical line was drawn beside clusters of spectrogram displaying similar shape. An arbitrarily chosen representative spectrogram is shown on the right of each cluster (range from 0 to 22050 Hz; fast Fourier transform, 256 bands; window, Hamming 50% overlap; frequency resolution, 86 Hz; temporal resolution, 5 ms).

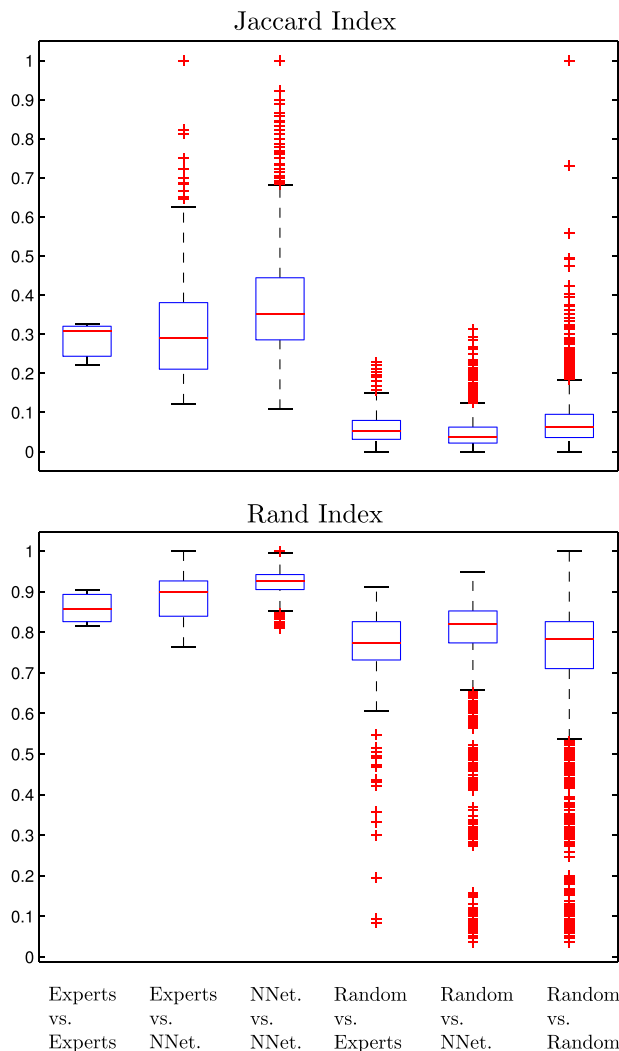


FIG. 6. (Color online) Distribution of the JIs and RIs. Three human expert classifications and 100 random and ANN (NNet.) classifications are compared. Boxes represent the 25th and 75th percentiles with median. The 100 replicates of automatic classifications are highly similar and more similar to expert classifications than expected by chance.

ANN algorithm to determine the number, as well as the composition of the song clusters. This ANN relies on a measure of bioacoustic distance that is in agreement with most available methods (Ranjard *et al.*, 2010) and is therefore suitable for exploratory analyses. A previous study that applied ANN algorithms demonstrated that supervised ANNs and LDA perform equally well in classifying black-capped chickadee call note types (Dawson *et al.*, 2006) and ANNs can, in some cases, outperform LDA (Mielke and Zuberbühler, 2013). Our results show that an unsupervised ANN algorithm, which does not require an informed training stage, can also be used to efficiently classify songs. The network self-organizes on the dataset using nonlinear relationships between acoustical parameters to uncover high-dimensionality structure, i.e., song variant clusters.

Several factors may explain the disagreement measured between human-based classifiers. Experts potentially pay attention to different visual and auditory features of the song recordings and spectrograms. Variability can also occur throughout the process of classification (Jones *et al.*, 2001).

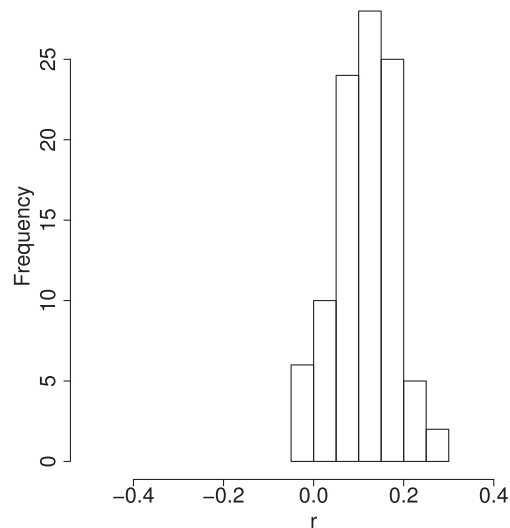


FIG. 7. Distribution of the Pearson correlation coefficient between repertoire and geographic distances obtained with 100 classification replicates of the 1879 songs dataset.

Such results could be produced in the presence of a subset of songs with a high level of similarities or dissimilarities and another set of songs more homogeneous. Experts would consistently classify the first set in the same way. However, the classification of the second set would diverge across expert classifications. Overall, these results illustrate the difficulty in classifying hihi male songs. Because our classification algorithm is fully automatic, it provides a tool to easily generate multiple classifications. We use such an approach in an attempt to integrate over the variation in the song variant clustering illustrated by the conflicting expert classifications. Variation between automatic ANN classifications can arise when conflicting signals of similarity are present in the distinct sound parameters used for the song encoding. While some parameters may be relevant to the species under study, others may not or could be generated by background noise. Integrating over a distribution of song classifications, instead of a unique or a limited number of expert-generated classifications, offers the possibility to take classification uncertainty into account in bioacoustic studies. More robust analyses will result from such an approach while gaining confidence in the results.

A remaining question is to understand the evolutionary or the behavioral causes explaining such song variation. In birds, vocal communication variation within a population can have a variety of functional significances (Catchpole and Slater, 2008). A diversity of messages usually related to mate attraction and territorial defense can be conveyed (Kroodsmas and Byers, 1991). Low level of correlation was reported between geographic distance and territory song variant repertoires. Such results may be purely due to chance, although geographic song variation may be present, but difficult to detect because of the small size of the island and a limited sample size. Most of the territory is indeed located in close proximity from each other on the island. Several hypotheses can be advanced to explain patterns of geographic song variation (Podos and Warren, 2007). For example, geographic

song variation can be the consequence of a biased dispersal behavior. Alternatively, the Tiritiri Matangi Island population could be at the initial stage of micro-geographic song variation, potentially leading to the development of geographic dialects because of specific learning patterns. The pattern of variation could also be directly related to the genetic diversity of the bird population with genetically related individuals acquiring proximate territories. Therefore, the study of genetic relatedness and dispersal behavior is required in this species to fully understand the causes responsible for the observed pattern of song variation.

V. CONCLUSION

We applied an automatic methodology for bird song detection and classification. High consistency is reported between song classifications generated automatically. While human expert classifications show some level of disagreement, they present higher clustering similarity with automatic song classification than random classifications. We, therefore, demonstrate that laborious visual or acoustic inspection of song recordings and spectrograms could be substituted by computational statistical learning programs. Moreover, our approach potentially offers a means to analyze a large amount of data generated by recent high throughput field recording technologies. Finally, we argue that integrating over classification replicates should be performed in order to account for song clustering uncertainty. Robust analysis is then made possible by studying the distribution of a statistic of interest rather than a single estimated value.

ACKNOWLEDGMENTS

The authors thank Kate Richardson for providing the GPS location of the nest boxes. Isabel Castro provided field assistance and helpful comments on the manuscript. Our thanks go to John Ewen, Rose Thorogood, and Tamara Henry for access to reproductive data and to the Supporters of Tiritiri Matangi for assistance with data collection. All data collection was carried out with permission from The University of Auckland Animal Ethics Committee and the New Zealand Department of Conservation. This study was supported, in part, both by the Marsden Fund Council from New Zealand Government funding, administered by the Royal Society of New Zealand, and by the Allan Wilson Centre for Molecular Ecology and Evolution. The authors wish to acknowledge the Centre for eResearch at the University of Auckland and New Zealand eScience Infrastructure high-performance computing facilities.

¹http://www.bioinformatics.auckland.ac.nz/dtwave_cluster.php (Last accessed 29/04/2015).

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